Renewable and Sustainable Energy Reviews 39 (2014) 1005–1011

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Potential of radial basis function based support vector regression for global solar radiation prediction

Zeynab Ramedani [a], Mahmoud Omid [b,*], Alireza Keyhani [b], Shahaboddin Shamshirband [c], Benyamin Khoshnevisan [b]

[a] Department of Agricultural Machinery Engineering, Faculty of Agricultural, University of Tabriz, Tabriz, Iran
[b] Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, University of Tehran, Karaj, Iran
[c] Department of Computer Science, Chalous Branch, Islamic Azad University (IAU), 46615-397 Chalous, Mazandaran, Iran

ARTICLE INFO

Article history:
Received 24 January 2014
Received in revised form
14 May 2014
Accepted 10 July 2014
Available online 9 August 2014

Keywords:
Renewable energy
Solar energy
Artificial intelligence
Support vector machine

ABSTRACT

Among the different forms of clean energies, solar energy has attracted a lot of attention because it is not only sustainable, but also is renewable and this means that we will never run out of it but the potential of using this form of renewable energy depends on its accessibility. Due to the fact that the number of meteorological stations where global solar radiation (GSR) is recorded, is limited in Iran we were meant to develop four distinctive models based on artificial intelligence in order to prognosticate GSR in Tehran province, Iran. Accordingly, the polynomial and radial basis function (RBF) are applied as the kernel function of Support Vector Regression (SVR) and input energies from different meteorological data obtained from the only station in the studied region were selected as the inputs of the model and the GSR was chosen as the output of the models. Instead of minimizing the observed training error, SVR_poly and SVR_rbf attempt to minimize the generalization error bound so as to achieve generalized performance. The experimental results show that an improvement in predictive accuracy and capability of generalization can be achieved by the proposed approach. The calculated root mean square error and correlation coefficient disclosed that SVR_ rbf performed well in predicting GSR. Comparing SVR_rbf results with SVR_poly, ANFIS, and ANN reveals that SVR_rbf outperforms the POLY model in terms of prediction accuracy.

Contents

* Corresponding author.
E-mail address: omid@ut.ac.ir (M. Omid).

http://dx.doi.org/10.1016/j.rser.2014.07.108
1364-0321/

1. Introduction

For decades, there has been a positive correlation between urban air quality and fossil fuels such as oil, gas, and coal. In other words, production and consumption of different types of fossil fuels for producing energy pose significant environmental challenges. Other sources of energy comprise “clean or renewable energy,” such as bioenergy, geothermal energy, run-of-the-river, wind power and solar energy. Our energy choices affect the air we breathe and the global atmosphere. Policy approaches must align energy and environmental issues to ensure that economic growth and environmental protection are achieved simultaneously. The administration challenge must be maximizing the benefits gained from energy consumption while minimizing the costs incurred.

Among the different forms of renewable energy, solar energy has attracted a great deal of attention because it is not only sustainable, it is renewable and this means that we will never run out of it [1–3]. It is about as natural a source of power as it is possible to generate electricity. The creation of solar energy requires little maintenance. Once the solar panels have been installed and are working at maximum efficiency there is only a small amount of maintenance required each year to ensure they are in working order [4–8]. The potential of clean energy in a region depends on its accessibility. The yearly average solar radiation in Tehran province—a province in the center and the capital of Iran – is about 4.92 kWh/m^2 day [9]. This abundance of solar energy helps energy policy makers to develop solar energy systems (solar power plants and solar heating systems), which are attractive alternatives to traditional power plants that burn fossil fuels such as oil and coal. Also, agricultural systems such as greenhouses, chicken farms, and dairy industry, are of the largest consumers of heating energies. Installation of solar energy systems with the aim of supplying heating need or required electricity can help us to achieve economic efficiency and reduce the emission of greenhouse gases.

To design and implement every solar power system an accurate detailed long-term knowledge of available global solar radiation (GSR) data in various forms, depending on the related application, is needed [10]. In Iran, the number of meteorological stations where global solar radiation (GSR) is recorded, is limited [11]. Moreover, even at these stations, there may be many days when GSR data are missing or lie outside the expected range. On the other hand, analysis of GSR and meteorological field can be performed with experimental techniques because it is very difficult and time consuming to measure GSR at meteorological stations. Thus, soft programming techniques (Artificial neural Network, Fuzzy-logic, Adaptive-Network-Based Fuzzy Inference System, etc.) can be used as powerful tools to analyze and predict GSR. Several researchers have used these techniques to estimate GSR as a function of meteorological data and a lot of predictive methods have been developed by them around the world.Jiang [12] developed an ANN model for estimating monthly mean daily global solar radiation of 8 typical cities in China. It is found that the solar radiation estimations by ANN are in good agreement with the measured values and are superior to those of other available empirical models. In a comprehensive research in Andalusia (Spain) Linares-Rodríguez et al. (2011) present a high correlation coefficient predictor GSR model with four meteorological data included: total cloud cover, skin temperature, total column water vapor and total column ozone for nine years from 83ground stations spread over the region. They used this data as input of ANN technic and GSR as output [13]. Voyant et al. [14] tested three single methodologies in clouding multi-layer perceptron (MLP), auto-regressive and moving average (ARMA), and persistence models in order forecast GSR. They concluded that the hybridization of the three predictors (ARMA, MLP and persistence) produced better results. In Saudi Arabia, Benghanem and Mellit [15] applied Radial Basis Function network (RBF) for modeling and predicting the GSR. In their research, it was found that in RBF-models sunshine duration and air temperature as input parameters were the most important parameters in the prediction of GSR. In another research study conducted by Wu et al. [16], it was proposed that a genetic approach combing multi-model framework be used for solar radiation time series prediction. Mostafavi et al. [17] developed new prediction equations for the GSR using an integrated search method of genetic programming (GP) and simulated annealing (SA), called GP/SA by the monthly data. These models are a step in progressing renewable energy plants. For example Hernandez et al. (2012) and Laidi et al. (2013) used GSR as one of the inputs of a model for prediction coefficient of performance (COP) of a solar intermittent refrigeration system for ice production [18,19]. Thus planting a GSR predicting model in each model is useful for future environmental planning.

This review literature shows the valuable application of artificial intelligence in the field if solar radiation modeling, thus, it was decided to explore the possibility of these techniques for developing a unified correlation for predicting GSR in Tehran province. Support vector (SV) method, which analyze data and recognize patterns and is used for classification and regression analysis, provides a universal new tool for solving multi-dimensional function estimation problems [20]. Some researchers used support vector machine (SVM) and support vector regression (SVR) for developing GSR predictor models. Zeng and Qiao [10] proposed a least-square (LS) support vector machine (SVM)-based model for short-term solar power prediction (SPP) in the USA. The inputs of the model were historical data on atmospheric transmissivity sky cover, relative humidity, and wind speed. The output of the model was the predicted atmospheric transmissivity, which then was converted to solar power according to the latitude of the site and the time of the day. Their results demonstrated that the proposed model not only significantly outperformed a reference autoregressive (AR) model but also achieved better results than a radial basis function neural network (RBFNN)-based model in terms of prediction accuracy. In other studies, the feasibility of SVMs in estimating solar radiation using air temperatures and sunshine duration was examined [21,22].

This paper aims to present feasibility applying radial basis SVR to predict global solar radiation based on some simple meteorological data.

2. Material and methods

2.1. Study area and data set

Difficulties in measuring GSR and the uncertainty of the measured data have been caused considerable effort to be undertaken to develop procedures and software for prediction and quality assessment of these data. Such assessments are needed to ensure that the data selected for various applications are of the highest quality available. Except GSR, other meteorological data are parameters that are routinely recorded at a large number of climatological stations (manned and automatic), due to the low cost of the respective recording instrumentation and the ease of data acquisition.

Tehran province with an area of 730 square km was selected as the study area. This province is located in 35 °N latitudes and 51° West longitude, in the north central of Iran. Measured daily data belonging to a seven-year period (1994 to 2000) was collected from the Islamic Republic of Iran Meteorological Office data center [11]. This is the solo station in Tehran province. The yearly average of solar radiation in the studied region is 4.92 kWh/m^2 day [9]. The monthly mean daily temperature ranged from a minimum

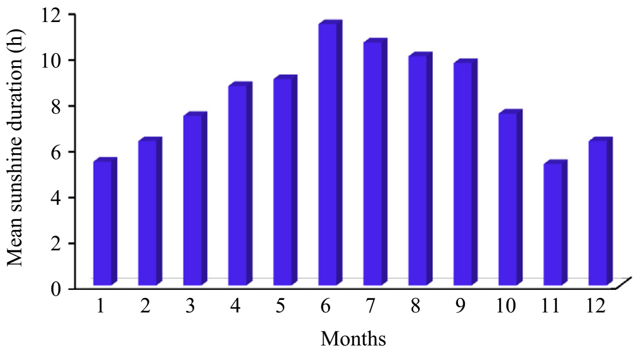

Fig. 1. Mean sunshine duration for selected station.

of −1.5 °C in January to a maximum of 33.9 °C in July [11]. The area gets sufficient bright sunshine hours throughout the year. The average bright sunshine hours are about 8–9 h per day. Yearly average sunshine durations for selected station are depicted in Fig. 1.

Maximum and minimum temperature, the actual duration of sunshine (n, hour), daylight hour (N, hour) that is the maximum possible duration of sunshine, number of days between 1 (January 1st) and 365 or 366 (December 31st), clear-sky solar radiation ($R_{so,}$ MJ/m^2 day) and extraterrestrial radiation (R_a, MJ/m^2 day) are some of the most important daily parameters that affect the solar radiation. In this study, these parameters have been selected as inputs of the developed model to find the best relation between them and solar radiation (output of the model). The extraterrestrial solar radiation that is the solar radiation received at the top of the earth's atmosphere on a horizontal surface, for each day of the year and for different latitudes can be estimated by following equation [23]:

$$R_a = 24 \times 60/\pi[\omega_s \sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\sin(\omega_s)]G_{sc}d_r \tag{1}$$

where R_a is the extraterrestrial radiation (MJ/m^2 day), ω_s is the sunset hour angle (rad), φ latitude (rad) that is positive in the northern hemisphere and negative in the southern hemisphere, δ is the solar declination angle (rad),G_{sc} is solar constant that is equal to 0.0820 MJ/m^2 min, d_r is an inverse relative distance of earth-sun (dimensionless). The expressions for d_r, δ, and ω_s can be found in reference [24].

R_{so} is fraction of extraterrestrial radiation reaching the earth on clear-sky days ($n=N$). This parameter can be calculated as:

$$R_{so} = (0.75 + 2 \times 10^{-5}z)R_a \tag{2}$$

where z is station elevation above sea level (m) [23].The training and validation data sets were selected by the randomization of the input data.

2.2. Supervised machine learning

SVMs are a type of supervised machine learning technique that is part of a generalized linear classifier family. The formulation contains the structural risk minimization (SRM) concept, as a contrary to the empirical risk minimization (ERM) approach that is widely employed in the statistical learning methods. SRM mitigates an upper bound on the generalization error, unlike the ERM which makes the error minimal in the training data. It is this difference that lends support to the SVMs with a greater potential to generalize. Furthermore, the solutions offered by the classical neural network models may be prone to fall into a local optimal solution, whilst a global optimum solution is assured for SVM. SVMs can be used in both problems with regards to classification and regression.

2.2.1. Feature space and kernel functions

The fundamental working principle of the SVMs is to perform the data-mapping in some other dot product spaces (called the feature space) through a non-linear mapping and perform the linear algorithm in the feature space. As it involves the evaluation of a dot product, the feature space is characterized by its highly dimensional nature and thus it necessitates high computational resources and time. In some cases, nonetheless, a less-complex kernel should be formulated and its efficiency assessed. Complex issues in the real world need a more expressive hypothesis space than the linear functions, as the already-existing linear learning machines are constrained by their computational superiority. To put in other words, the target data lack the ability to be expressed as a simple linear combination of the given attributes. One significant property of linear learning machines lies in its ability to be expressed in a dual representation. It indicates that the hypothesis could be expressed as a linear combination of the training points, in order for the decision rule to be able to be assessed with merely the inner products between the test point and the training points. If there is the availability of a way of computing the inner product in feature space directly as a function to the original input points, there is a possibility that a non-linear learning machine is built, and it is known as a direct computation method of kernel function, which is denoted by K. Alternatively speaking, a kernel function can be interpreted as a function k, such that for all $x, z \in X$,

$$K(x,z) = \langle \varnothing(x)\varnothing(z)\rangle \tag{3}$$

There are two basic conditions of a kernel function, (3) the function has to be symmetric, i.e.

$$K(x,z) = \langle \varnothing(x)\varnothing(z)\rangle = \langle \varnothing(z)\varnothing(x)\rangle = K(z,x) \tag{4}$$

and (4) it must meet the Cauchy–Schwartz inequality.

$$K(x,z)^2 = \langle \varnothing(x)\varnothing(z)\rangle^2 \le ||\varnothing(x)||^2||\varnothing(z)||^2 \tag{5}$$

In the above equations, despite it being necessary, however, to promise a feature space as defined by the kernel function is not sufficient. Nevertheless, once characterized, kernel representations provide an optional solution by projecting the data into a high-dimensional feature space to enhance the computational capability of the linear learning machines. From the multiple kernel functions available to develop a model, nonlinear kernel functions are likely to be more efficient in running an analysis on the intricate relations between various real-world issues and are therefore adopted in this current work. This study manipulates a type of SVM learning approach comprising of RBF kernel, to construct a model that ascertains the relation between values of global solar radiation as output and inputs included: maximum and minimum temperature, actual duration of sunshine, daylight hour, clear-sky solar radiation and extraterrestrial radiation. These input parameters are readily available in most of meteorological stations and can be helpful for estimation GSR.

2.2.2. Radial basis function as kernel

The flexible nature of the SVM is attributed to the usage of kernel functions that implicitly chart the data to a higher dimensional feature space. A linear solution in the higher dimensional feature space corresponds to a non-linear solution in the original, decrease dimensional input space. This makes SVM a choice that is feasible for addressing various issues, which are naturally nonlinear [25]. There are some accessible methods which employ the non-linear kernels inside their strategy towards regression problems, simultaneously applying SVMs [26]. One specific method requires using the radial schedule function (RBF) known as LS-SVMs. The main benefit of LS-SVM is that it is computationally more efficient than the customary SVM method, since the LS-SVM

training needs only the solution of a set of linear equations instead of the lengthy and computationally demanding quadratic programming problem that is entailed in the standard SVM. To compare with other probable kernel features, the RBF is a more compressed, supported kernel and this makes it very suitable to restrict the computational training process and improve the generalization efficiency of LS-SVM, an attribute of great value in the model designing. Therefore, the RBF, with the parameter σ, is adopted in this study.

2.2.3. Support vector regression (SVR)

ε-support vector regression (SVR) was put forth as an optional ε-insensitive loss function. The objective held by SVR is to search for the function with the most ε deviations from the real destination vector for all training information received and which must be as flat as possible. The Kernel function is recognized for its concept of the non-linear support vector regression. SVR needs to have fewer established user-defined parameters for establishing kernel-specific parameters. To add, the optimal values of the legalization argument C and size errors in sensitive area ε need to be ascertained. The settings' selection controls the complexity of the prediction. One of the major advantages of SVR lie in the algorithm which includes the resolution of the quadratic programming function leading to a distinctive, optimum and thorough solution.

In SVR, $\{x_i, y_i\}_{i=1}^{N}$ is considered as a training set, in which $x_i \epsilon \Re^p$ represents a ρ-dimensional input vector and $y_i \epsilon \Re$ is a scalar measured output that denotes the system output. The goal is to develop a function $y = f(x)$ which represents the output dependence y_i on the input x_i. The form of this function is:

$$y = w^T \varphi(x) + b \tag{6}$$

where w is known as the weight vector and b the bias. This regression model can be constructed using a nonlinear mapping function $\phi(\cdot)$. By mapping the original input data onto a high-dimensional space, the non-linear separable problem shifts into being linearly separable in space. The function $\phi(\cdot) = \Re^p \rightarrow \Re^h$ is largely non-linear function which maps the data into a higher, possibly infinite, dimensional feature space. The main difference from the standard SVM lies in the fact that the LS-SVM involves equality constraints instead of inequality constraints, and works with the least squares cost function. The optimization problem and the equality constraints are interpreted by the following equations:

$$\min J(w, e) = \frac{1}{2} w^T w + \gamma \frac{1}{2} \sum_{i=1}^{N} e_i^2 \tag{7}$$

subject to

$$y_i = w^T \varnothing(x_i) + b + e_i, \quad i = 1, \ldots, N \tag{8}$$

where e_i is the random error and $y \epsilon \Re^+$ is a regularization parameter in optimizing the trade-off between minimizing the training errors and the model's degree of complexity. The objective is now to search for the optimal parameters that minimize the prediction error of the regression model. The optimal model will be selected by making minimal the cost function where the errors e_i are minimized. This formulation corresponds to the regression in the feature space and, owing to the fact that the dimension of the feature space is high, even possibly infinitive; this problem does not have an easy solution. Therefore, to address this, the following Lagrange function is expressed:

$$L(w, b, e; \alpha) = J(w, e) - \sum_{i=1}^{N} \alpha_i \{ w^T \varnothing(x_i) + b + e_i - y_i \} \tag{9}$$

The solution of Eq. (9) is obtainable by making partial differentiation with regards to $w, b, e; \alpha$, *i.e.*

$$\frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{N} \alpha_i \varnothing(x_i) \tag{10}$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow b = \sum_{i=1}^{N} \alpha_i = 0 \tag{11}$$

$$\frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \gamma\, e_i, \quad i = 1, \ldots, N \tag{12}$$

$$\frac{\partial L}{\partial x_i} = 0 \rightarrow w^T \varnothing(x_i) + b + e_i - y_i = 0, \quad i = 1, \ldots, N \tag{13}$$

Last but not least, the estimated values of b and α_i, i.e. $\hat{b}$ and $\hat{\alpha_i}$, can be obtained by solving the linear system and the consequent LS-SVM model can be expressed as follows:

$$y = f(x) = \sum_{i=1}^{N} \hat{\alpha_i} K(x, x_i) + \hat{b} \tag{14}$$

where $K(x, x_i)$ is a kernel function. In this case, the non-linear RBF kernel is defined as:

$$K(x, x_i) = exp\left(-\frac{1}{\sigma^2} ||x - x_i||^2 \right) \tag{15}$$

where σ is the kernel function parameter of the RBF kernel. The regularization parameter γ is also important in the LS-SVM model and it determines the trade-off between the fitting error minimization and the smoothness of the estimated function. It is not known earlier on which γ and σ are the best for a particular application issue to achieve the maximum performance with LS-SVM models. The value of the kernel function has to be tuned during the calibration of the model. A prediction model based on the support vector regression (SVR) is being suggested in this paper as a way to predict solar radiation. Aiming to develop an effective SVR model, the SVR parameters must be established with care. SVR seeks to minimize the generalization error to gain generalized performance instead of minimizing the training error.

2.3. Artificial neural network

In order to evaluate the suggested model, artificial neural network (ANN) was developed and the results obtained from ANN were compared with the results gained from SVM [27]. To train ANNs seven independent variables were considered as inputs and solar radiation was selected as only output. The network was trained using 75% of the original 3707 experiments and the remaining 25% of the rest was applied to create a test dataset. Matlab software was employed and ANN toolbox was utilized in order to develop a feed-forward neural network with one, two and three hidden layers.

The input layer corresponded to the seven selected input parameters. The output layer corresponded to the one output, i.e., the measured solar radiation. These networks were trained using the Levenberg–Marquardt training algorithm. Here, the neural network trained with Levenberg–Marquardt algorithm was termed as Levenberg–Marquardt neural network (LMNN).

Table 1
Performance criteria.

Criteria	Calculation	
Root mean squared error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (d_i - y_i)^2}$	(16)
Correlation coefficient (R)	$R = \frac{\sum_{i=1}^{n} (d_i - \overline{d}_i)(y_i - \overline{y}_i)}{\sqrt{\sum_{i=1}^{n} (d_i - \overline{d}_i)^2 \sum_{i=1}^{n} (y_i - \overline{y}_i)^2}}$	(17)

Table 2
User-defined parameters for SVR_rbf, SVR_poly.

Support vector regression	RBF kernel			Polynomial kernel		
	C	*γ*	*e*	*C*	*d*	*e*
	100	0.3	0.001	100	1	0.001
ANFIS	Number of rules:10, membership function: generalized bell, number of iteration:1000, identification methods:grid partitioning					
ANN	Learning rate = 0.2, momentum = 0.1, hidden nodes = 7,12, number of iterations = 1500					

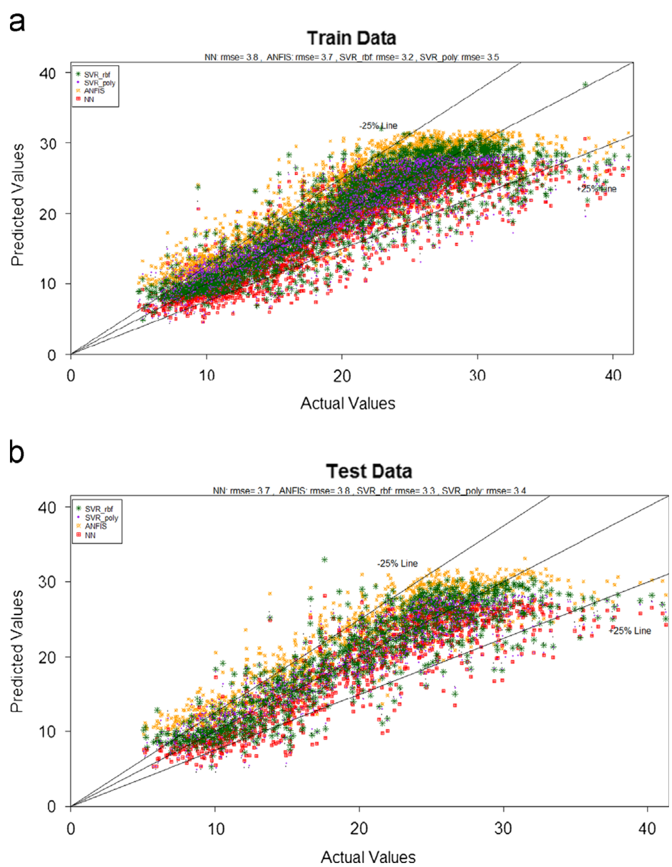

Fig. 2. Plot of observed and predicted solar radiation with the original data set using SVR_rbf and SVR_poly model during training (a) and testing (b).

2.4. Performance metrics

To evaluate the performance of the rbf-svr and poly-svr model several measures were used to confirm the validity of the proposed SVR models, and ANN. The root mean squared error (RMSE) served to evaluate the differences between the expected and actual values. The parameters are calculated as indicated in Table 1.

where n is the total number of test data, d_i is experimental value and y_i is forecast value. $\overline{d}_i$ is averaged experimental value and $\overline{y}_i$ is averaged forecast value.

3. Results and discussions

RBF was applied as the Kernel function for the prediction of solar radiation in this study. The three parameters associated with RBF Kernels are C, e and r. SVM model accuracy is principally dependent on the model parameter selection. In our scheme, a default value of $e=0.1$ seemed to perform well. To select user-defined parameters (i.e. C, d and g), a large number of trials were carried out with different combinations of C and d for polynomial kernels and C and g for radial basis function kernels. Table 2 provides the optimal values of user-defined parameters for this dataset with polynomial and RBF kernel-based SVR. For a reasonable appraisal of outcomes with both RBF and polynomial kernels, a similar parameter e value was applied with SVR.

Table 3
Performance indices of various approaches.

Method	Training		Testing	
	Error (RMSE)	Coefficient of determination (R)	Error (RMSE)	Coefficient of determination (R)
SVR_rbf	3.2	0.900	3.3	0.889
SVR_poly	3.5	0.883	3.4	0.887
ANFIS	3.7	0.897	3.8	0.899
ANN	3.8	0.895	3.7	0.894

To evaluate SVR model performance, observed solar radiation was plotted against the predicted ones. Fig. 2(a) illustrates the results with the performance indices between observed and predicted data in the training phase, while Fig. 2(b), indicates the results for the testing phase, respectively. Generally speaking, as seen from Fig. 2, SVR_ rbf performed well in predicting GSR. Comparing SVR_rbf results with SVR_poly, ANFIS, and ANN reveals that SVR_rbf outperforms the POLY model in terms of prediction accuracy.

To evaluate the performance of the proposed method, experiments were conducted to determine the relative significance of each independent parameter (input SVR) on the solar radiation (output). The root mean squared error (RMSE) and correlation coefficient (R) served to evaluate the differences between the expected and actual values for SVR_poly and SVR_rbf. Table 3 compares the SVR_rbf with SVR_poly models. The results in Table 3 prove that proposed model is capable of predicting solar radiation with minimal error and the highest accuracy.

As it was discussed, SVR models are the best model for the prediction of solar potential in Tehran province. It could be said that determining of GSR distribution is the most important parameter for designing and selection of solar systems not only for reducing high initial cost of them but also for increasing collection of energy. At present, such systems are not economically viable in agricultural buildings such as greenhouses without carbon trading option taken into account. Therefore, government support through financial investment and subsidy is an effective way for extending these systems in agricultural sections [24].

To make sure that the developed models can be generalized to all the Tehran Province, the best network (SVR-rbf) was employed to simulate new data set obtained by Karaj station in year 2008. This station is located in the west of Tehran in 35 °48′N and 51 °00′E in latitude and longitude respectively. The results showed that the model successfully predicted GSR using new data set from another station. The correlation coefficient between observed and predicted GSR was 0.93 (Fig. 3(a)). As can be observed in Fig. 3 (b) the predicted value can follow their actual ones with high accuracy and minimal error. Accordingly, it can be concluded that

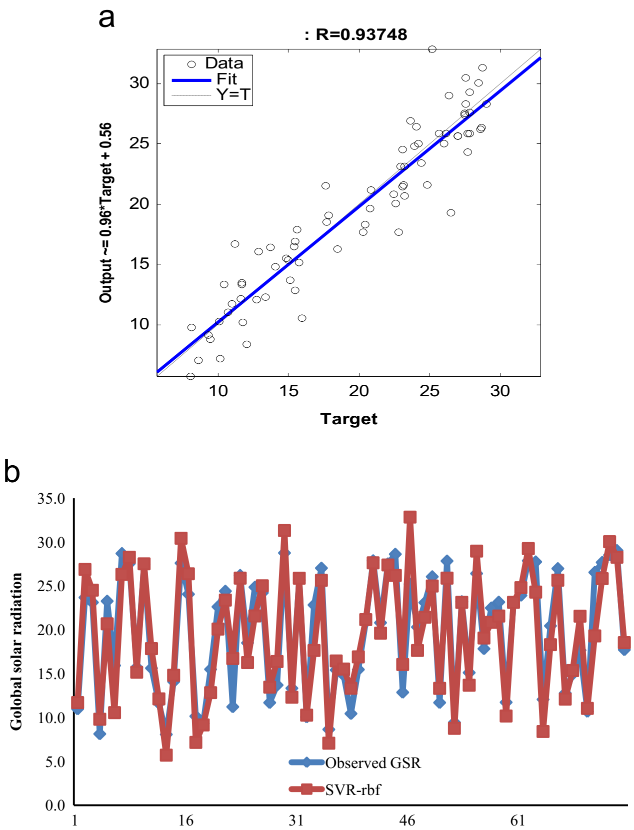

Fig. 3. Observed GSR verses predicted GSR based on the best developed model.

the developed model can be used through the Tehran Province to forecast GSR based on meteorological data.

4. Conclusions

This paper presents a support vector regression (SVR) technique to present a model for prediction global solar radiation (GSR). This model addresses the technical methodology of examining the potential for the suitability of energy supply plants and renewable energy latency in a region for support material for urban energy supply planning in the draft plan development stage. One of the main characteristics of SVR technic in this model is that instead of minimizing the observed training error, SVR attempts to minimize the generalized error bound so as to achieve generalized performance. Two SVRs were investigated: the first one is a radial basis function (SVR-rbf) and the next is a polynomial function (SVR-poly). The result showed that the SVR-rbf is better than SVR-polt in predicting GSR. The performance of the SVRs approaches against the results provided by ANN and ANFIS obtaining interesting improvements in the prediction system. Both techniques are better than ANN and ANFIS in terms of root mean square error. However, estimated results by SVR produce remarkably smaller estimation errors compared to ANNs. Moreover, SVR takes lesser computer time than ANN and ANFIS for the two cases. From the results it can be concluded that SVR method can predict GSR with higher estimation accuracy and shorter computation time.

The experimental results show that an improvement in predictive accuracy and capability of generalization can be achieved by our proposed approach. Results show that SVR can serve as a promising alternative to existing prediction models. It can be seen from the experiment that the prediction model overcomes the main shortage of artificial neural network without defining network structure and trapping in the local optimum.

Acknowledgment

The financial support provided by the University of Tehran is duly acknowledged.

References

[1] Janjai S, Prathumsit J, Buntoung S, Wattan R, Pattarapanitchai S, Masiri I. Modeling the luminous efficacy of direct and diffuse solar radiation using information on cloud, aerosol and water vapor in the tropics. Renew Energy 2014;66:111–7.
[2] Ming T, de_Richter R, Liu W, Caillol S. Fighting global warming by climate engineering: Is the Earth radiation management and the solar radiation management any option for fighting climate change? Renew Sustain Energy Rev 2014;31:792–834.
[3] Hove T, Manyumbu E, Rukweza G. Developing an improved global solar radiation map for Zimbabwe through correlating long-term ground- and satellite-based monthly clearness index values. Renew Energy 2014;63:687–97.
[4] Khorasanizadeh H, Mohammadi K, Mostafaeipour A. Establishing a diffuse solar radiation model for determining the optimum tilt angle of solar surfaces in Tabass, Iran. Energy Convers Manage 2014;78:805–14.
[5] Anastácio PM, Marques B, Lillebø AI. Modeling the effect of temperature, solar radiation and salinity on *Bolboschoenus maritimus* sequestration of mercury. Ecol Modell 2013;256:31–42.
[6] Ronzio DA, Collino E, Bonelli P. A survey on different radiative and cloud schemes for the solar radiation modeling. Sol Energy 2013;98(Part B):153–66.
[7] Lauret P, Boland J, Ridley B. Bayesian statistical analysis applied to solar radiation modelling. Renew Energy 2013;49:124–7.
[8] Kisi O. Modeling solar radiation of Mediterranean region in Turkey by using fuzzy genetic approach. Energy 2014;64:429–36.
[9] RETScreen., Clean Energy Project Analysis Software, in, 2014.
[10] Zeng J, Qiao W. Short-term solar power prediction using a support vector machine. Renew Energy 2013;52:118–27.
[11] IRIMO. Islamic Republic of Iran Meteorological Office. Tehran, Iran: Data Center; 2000.
[12] Jiang Y. Computation of monthly mean daily global solar radiation in China using artificial neural networks and comparison with other empirical models. Energy 2009;34:1276–83.
[13] Linares-Rodríguez A, Ruiz-Arias JA, Pozo-Vázquez D, Tovar-Pescador J. Generation of synthetic daily global solar radiation data based on ERA-Interim reanalysis and artificial neural networks. Energy 2011;36:5356–65.
[14] Voyant C, Darras C, Muselli M, Paoli C, Nivet M-L, Poggi P. Bayesian rules and stochastic models for high accuracy prediction of solar radiation. Appl Energy 2014;114:218–26.
[15] Benghanem M, Mellit A. Radial basis function network-based prediction of global solar radiation data: application for sizing of a stand-alone photovoltaic system at Al-Madinah, Saudi Arabia. Energy 2010;35:3751–62.
[16] Wu J, Chan CK, Zhang Y, Xiong BY, Zhang QH. Prediction of solar radiation with genetic approach combing multi-model framework. Renew Energy 2014;66:132–9.
[17] Mostafavi ES, Ramiyani SS, Sarvar R, Moud HI, Mousavi SM. A hybrid computational approach to estimate solar global radiation: an empirical evidence from Iran. Energy 2013;49:204–10.
[18] Hernández JA, Rivera W, Colorado D, Moreno-Quintanar G. Optimal COP prediction of a solar intermittent refrigeration system for ice production by means of direct and inverse artificial neural networks. Sol Energy 2012;86:1108–17.
[19] Laidi M, Hanini S. Optimal solar COP prediction of a solar-assisted adsorption refrigeration system working with activated carbon/methanol as working pairs using direct and inverse artificial neural network. Int J Refrig 2013;36:247–57.
[20] Lin D-C, Guo Z-L, An F-P, Zeng F-L. Elimination of end effects in empirical mode decomposition by mirror image coupled with support vector regression. Mech Syst Signal Process 2012;31:13–28.
[21] Chen J-L, Li G-S, Wu S-J. Assessing the potential of support vector machine for estimating daily solar radiation using sunshine duration. Energy Convers Manage 2013;75:311–8.
[22] Chen J-L, Liu H-B, Wu W, Xie D-T. Estimation of monthly solar radiation from measured temperatures using support vector machines—a case study. Renew Energy 2011;36:413–20.
[23] Allen, R.G., Pereira, L.S., Raes, D., Smith, M., 1998. Crop evapotranspiration guidelines for computing crop water requirements, FAO Irrigation an Drainage Papers, Rome, Italy, p. 326.
[24] Ramedani Z, Omid M, Keyhani A. Modeling solar energy potential in tehran province using artificial neural networks. Int J Green Energy 2013;10:177–91.

[25] Shamshirband S, Petković D, Saboohi H, Anuar NB, Inayat I, Akib S, et al. Wind turbine power coefficient estimation by soft computing methodologies: Comparative study. Energy Convers Manage 2014;81:520–6.

[26] Shamshirband S, Petković D, Amini A, Anuar NB, Nikolić V, Ćojbašić Ž, et al. Support vector regression methodology for wind turbine reaction torque prediction with power-split hydrostatic continuous variable transmission. Energy 2014;67:623–30.

[27] Celik AN, Muneer T. Neural network based method for conversion of solar radiation data. Energy Convers Manage 2013;67:117–24.